DIAGNOSIS
BASED ON INCOMPLETE CAUSAL MODEL

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by

JYOTIBIKAS BHATTACHARYA

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CERTIFICATE

This is to rtify that the thesis work entitled **Diagnosis Based On Incomplete Causal Model** has been carried out by Jyotibikas Bhattacharya und r my sup rvision and ha not been submitted elsewhere for a deg ee

(Dr R M K S ha)

Profess r

Dept of Computer Science

and Engineering

Ind an Inst t te of T hnology

Kanpur

July 1991

Kanpur

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ABSTRACT

In the pr sent work a mechanism for diagnosis of mult pl faults n a sy tem has been implemented The doma n knowledge s represented at the de p level by a causal network and at a shallow level by rules Two forms of ncompleten s a e accommodated in the model First the init al cau es or p turbations respo ible for the malfu ctioni g of th ystem under consideration are assumed to be non ver f able Secondly the relations CAUSES and HAM in the causal etwork may be incomplete and can be labelled a MAY denoting such incompl ten ss This second form of inc mpleten ss implie that certain conditions are being abstra t d The diagnost c process proceeds in iterat ons of set covers over the set of all observations The manifestations not obser ed are as umed to be absent The diagnostic process s *non monotonic* It can al o lead to multiple solutions The criterion of parsimony over initial causes has been used to generate a soluti n which ensures the assumption of minimum number of initial cause Such a solution has been t rmed an IC Parsimonious olution After having succeeded in generating such a solution based on reasoning in the deep level the system abstracts shallow knowledge from this in the form of rules When a diagnostic problem is posed the sy tem tries to ge erate a solution using the shallow knowledge If it does not succeed then it u es the deep knowledge t generate a solution

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Chapter 1

INTRODUCTION

Diagnosis is known to manki d from the dawn of ivilization I the beginning it started with med al d agnosis but later on as man de eloped different artifact he also had to d agnos their faults when they needed repair It so turns out that the huma physiological system be ause of its sheer complexity has remained the mo t enigmati of all ystems that require fault diag osi It is perhap because man has himself built the electron and mechanical systems that he understands the working of these sy t ms bett tha his own physiological syst m and hence can diagnose faults more precisely in case of the former Th indicates that some deep knowledge about the system helps one in diagnosing its faults But then how often do we u e or more rele antly in a position to have and hence use such deep knowledge about systems ? Indeed a faulty television is faster repaired by a TV mechanic rather than many an electronic g ne r who ha a deeper knowl dge about the system A mechan c s knowledge abo t the system is indeed superficial but his e perienc in diagnosis and the tricks of the trade learnt from his master equip him with lots of heuristic knowledge about associating manifestations of faults with subsystems that are faulty He does not have th lower level causal functional and physical information of the system but such knowledge is not needed in the more common

ca s However when a new problem appears the m ha ic s repe to r of knowledge fails to meet the situation That is when we need the deep knowledge of the engineer to fall back upon Somewhat sim lar itu tio prevails even in th case of medical diagnosis The doctor s exp rien e equips him with a lot of rule about correlating diseas s with their manife tat ons (ymptom of th disea es) First he tries to apply such knowledge to arrive at a d agnosis Only when he fails he falls back on his deep knowledge to carry out a d tailed diagnos That is the expert can reason from first principles if necessary to find a solution Thus in domains such as medical diagnosis deep knowledge must be modelled

Diagnostic problems have often been cast into a pattern recognition r tatistical d ci on th ory framework Computer repr sentation is not difficult and as a result many well-known methods such as those based on Baye Theo em have been used The difficulties with applying these methods (e g scarcity of statistics and the use of invalid approximations) are also sufficien ly persistent so that alternative approaches have been sought In many medical areas existing knowledge could nhance the decision making capabilities of a diagno tic system There are many useful decision rules specifi to a given medical application that the physician directly applies in his or her reasoning

The statistical methods extract the th decision making rules mplicitly from accumulated sample e p rience The approache bas d on Artificial Intelligence (henceforth abbrev ated as AI) attempts to capture such rules more explicitly and intend to o r me som of the limitations of purely statistical methods by developing a more structured representation for th diagnostic and the apy s lect on problems A program that uses decision trat g e based on explicit representations of medical knowledge can m re easily incorporate evolving changes in its k wl dge ba e dependent of the reasoning strategi s It can also incorporate the results of clinical experience by matching the more explicit patterns of reasoning to the decisions and opinions of physician Such systems are more likely to be accepted beca they are expressed in a decision making context familiar to the clinician A structured representation can also permit the formulation of complex hypotheses that express progression and severity of disease Some researchers have attempted to increase the scope a curacy and explanation capabilities of their y tems by increasing st u ture while t ll pre er ing a statistical framework Others have relied on logical and sema tic en odings of contextual knowledge within an artifi ial intell g nce framework

Several fundamental AI issues are raised by medical decision making problems One important issue concerns the development of representations that are powerful enough to capture a complex and

hanging knowledg base in a realistic task domain Method of acquiring knowledge from e perts th choice of appropriate le els of abstraction and resolution for de cribing a given p obl m and th hoice of a computer representat on of th knowledge base a e all problems that immediately ar se in developing such systems They a e losely linked to the control strategies or methods used to pr du e interpr tations for ind v dual case Fu damental to most such control strategies is the capability of app oximat r aso ing This is needed to manag the multiple hypoth es that can be generated from a la ge and complex knowl dge base which includes statements at different le els of uncertainty Once decisions are reached producing explanations becomes an impo tant task if the acceptability of the system is enhanced Practical ssues of implementation for th se la ge knowledge based systems include ease of knowledge management (updating) efficiency cho e of languages and transferability into practical use in both the original domain and other similar ones

The rapid evolution n digital technology has made problems related to testing digital systems particularly difficult to s lve Some of these problems deal with test ge eration fault diagnosis design for testability and checking for the compliance of design for test rules O er the last two d cades numerous systems have been developed to solve these problems However in order to develop more powerf l and po sibly mor efficient

syst ms re earchers have look d toward the use of AI and p cifically knowledge based t chn logy to provide new approa hes Fault d agn si deals with localization of faults or defects based on ob rv d system beha iou The diagnostic pr c requires knowledge about the hardwa e nd r diagnosis D fferent approach s requ d fferent types of knowledge In an e treme a if the sy tem ca be modelled as a chain of f ctionally dependent components m nimum knowledge is required for diagno By probing the output and input of each c mp nent in the ha n a troubleshooter can det rmine which component s faulty For example if th inp t t a component is det rmined to be correct and th output is observed to be incorrect then this component is assumed t b faulty The only knowledg required to diagno such a system is the dependency chain Reasoning is simple in this case However mo t systems do not have such a hain structure and thus require a mor complex diagnosti procedure For these cases much more k owledge about the system is q ired and AI techniques ar oft n employed in the diagnosti p ocess

The difficulti s encounter d in applying knowledg based systems technology t complex systems have mad the ne d for representing and using deep knowledge about system behaviour increasingly clear to designers This knowl dge is typically well structured formal relying on establish d theories As opposed to empirical

a o ational knowledge s ch k owl dge is said to p v d a deep mod l of the domain Ther has als b en att mpts to fo m a g al th ory of diagnosis f m f rst princ ples based on deep mod ls But such models rarely i corporate any f rm of incompleteness The pr ent work aim at identifying and epr senting the ca sal structure underlyi g a specific expertise with some forms of incompleteness incorporated in the representation formalism Some shallow knowledge in the form of ul i abstract d after reasoning in the deep m del and fi d ng out a pa simonious solutio

1 1 Organization of the Thesis

In chapter 2 a revi w of the related work is presented Different approaches are discus ed and examples are briefly described

In hapter 3 the theoretical basis of th impl mented system followed by a system level description of the implementation is presented

In chapt 4 the implementation details of the various mod les present in the diagnostic system are presented

In chapter 5 conclusions and direction toward future work are ndicated

Chapter 2

A REVIEW OF DIAGNOSTIC SYSTEMS

We pr t he a bri f eview of several diagnostic systems that have been d v loped o the y a B t befo e that let us have a look at what s in general involved n build g a diagnostic system

2 1 What is Involved in Building a Diagnostic System ?

Before build ng a d agnostic system one sh uld address the following que tion within the scope of a g ven application how can we define an observation what do we call a ymptom ? What do we call a fa lure a d how do we express it ?

A conceptual analysis f the diagnostic process undertaken from oncrete applications has led researcher to propose a triple problem breakdown viz observation interpretation qualif cation

It i obvio s that any diagnosis dep nds on the bs vation of a real object Th fore de cription capacities of what observed a e needed ither implicitly or explicitly All diagnostic syst ms nclude an implicit or explicit description language that defines and l m ts the information used by the system to carry the diagnosis

The cho e f this lang age is fundam ntal It can be ery abstract (value g aphs t ming diagram etc) and its deq acy will ond tion the final perf rmance In fact the system w ll try to make a d agnos on th mere basis of the phrases n the language The latte should be suffi ie tly complet to enabl the eas est diagnosi poss bl but not too mplex so as to simplify the obs vation process (indeed it is m ch easier to measure oltage tha to establish a timing diagram)

The data observation phase brings in the notion of correct frame of ref ence (or description of nom nal behaviour) The obse ved obj ct must be compared to a nominal model

For an electri al appliance the referen e could be a complet state graph In the case of an electronic board the correct function model may be an aggregate of equations that che ks the inputs and outputs of each elementary component By simulation one could then obtain th nominal state of the board given a test ector The comparison between the theoretical and measured values would then give the fault indexes

For more complex and non decomposable systems a symptomatol gical model can be used A patient may be said to be feverish by knowing that the normal state is the absence of fever a car engine that chatters by knowing that the normal state is a steady running rate The very term of symptom thus makes a refere ce to the observation of an abnormal state If the d scription capacit s of an object are limited to symptoms th

(impli t) ref r n e of c ect fun tioning i defined by th ab nce of any ymptoms This s a form of negati e r ference but it is not really different from a more constructive model like the equational model

Now to p form a diagnosis one bases it on the state of the bject and the xplicit or mpl c t comparison to a reference The then remains the pr blem of the fault d scription itself that we have called fault qualif cation Let us suppose that we have a numb r of observations and a eference at ur disposal and that we are in a position to check if that reference is respected or not If it is not we could limit oursel es by showing the incompatible measures and equat ons and to then state the fault is described by these obs rvations and this reference The execution of a diagnost c process as t is intuitively perceived must go f rther

For example with an electro ic board we do not want to show a d cription of diverg nces but to put a name to the component that is upposedly responsible for thes divergences What we mean here is failure qualification by component identif cation We ther fore fi ourselv a prior a supplementary con traint which is to merely d cr be the failure in term of components

In th same way in medicine an illness could be defined as a list of symptoms since each symptom is an anomaly in itself The qualification of failures in this case is by illness identification

Diagnostic pr blem d scription therefore passe by the pecification

of p rceptive capac ties

f a correct fun tion reference

of a failure qualification language

The d agnosis pro ess environment is then perfectly defined Th choice of the format of these ent tie is however totally subjective

Now an algorithm s to be written which manipulate the dat and makes th fault hypotheses ba ed on a nominal model of the observed obj t correspond to the observations

Algorithmic problems linked to this final stage may entail a rethinking of the the formats (sophistication to reduce the amount of work required of thinning down to simplify the algorithms)

In general the approach is mixed in that it is often known beforehand what typ of algorithm will be arr ved at (graph sear h pattern matching tc) and that th s information is us d to guide the choice of format

An effi ient strat gy fo fa lt diagn i reli s po specific symptoms to activate only a small po tion of the av ilable d agnostic knowledge However pe t y tems and human using this strat gy oft n comm t characteristic errors The errors commonly refer d to as gard n path rrors occur because significa tly differe t faults may manifest s m lar symptom If these symptom ar co fused the wrong port n of d ag o t c knowledge ca be activated Th Galen Expert System [Moen88] investigates occurr nce of such er rs a d des ribes a strategy for redu ing their occ rr nce

2 2 Deep versus Shallow Knowledge

Two ma j types of knowledge are commonly used in diag o t c reasoning namely shallow knowledge and d ep knowledge

Shallow knowledge refers to the empirical knowledge of human experts in the association of the observed symptoms which is the discrepancies between the predicted and observed behaviour with system faults This knowl dge is usually based upon prior mach ne deductions stati tical intuition o the past experience of human exp rts It is primarily heuristic and is lim ted in a specific domain Such knowledge often r sults in impressive performance when it is of the form whi h can be put into a rule format Howev r outside the scope of expertise of the knowledge source the performance is poor Also shallow knowledge often does not take into account the structure or design of the system being

d agnosed E amples of such sy t ms are MIND (develop d by A J Wilkinson et al) MYCIN (developed by E Shortliffe et al) ATEX (d veloped by M B Bassant et al) t

Deep knowledge refers t knowledge about th stru ture and b havio of the system u d test in addition to kn wledge of diagnostic methodologies R a o ng directly from de p knowledge oft n refer ed to as first pr nciples or model bas d reason ng Descriptio s of the system st uct re and behaviour are used which can exist in mult ple levels of abstra tion The knowledge is de p in the sense that it is possible to explain the misbehaviour d wn to very low lev l components of the system a long as that level of descriptio is available Examples of su h y tems are GDE (developed by J De Klee et al) CASNET ([Weiss78]) [Reiter87] etc

Some diagnostic systems use both deep and shallow knowledg Th shallow kn wledge is first used to relate symptoms to possible causes of the malfu ction and suppl e appropriate testi g information If th process fails the ystem then uses d p knowledge The comb ned knowledge ca b used to diagnose ystem efficiently Examples of u h systems are [Hanna88] IDM [Fink87] SIDI [Ayeb88] etc

2 3 Diagnostic Systems Some Examples

We take up some example systems each of which uses one of the approaches described in the previous s ct on

2 3 1 The MYCIN System

MYCIN [Clancey84] is an interactiv prog am des gn d t be used as a consultant n d ffi lt cas s of meni gitis or ba t remia It suggests a set of likely organisms (bacteria) and ther p op th apy that will treat those that are most gnif cant MYCIN was one f the first r l ba ed e pert y tems The domain knowledge of MYCIN i r p es nted in a set of about 500 production rule Mo t of the rule encode as o ations between findings and a hypothesis P oblem s l ing b haviour could be modified by altering a rul f adding new ones However valuable knowledge abo t d ea e taxonomy ause and effect and temporal ordering between disorders are represented only implicitly som what buried in rules This frustrated attempt t use MYCIN s rules for intelligent mp t r aided instruction MYCIN backward chains th ough the rule base although for reasons of efficiency rules are at times invoked in a data directed fashion Rules were meant to represent only domain knowledge but ultimately they do n de a good deal of control l gic as well Meta-rules ar used fo controlling the invocation of bj t rul Meta-rules are associated w th clinical parameters they are strategy ul s which suggest the best app ach to establ sh the value/s of the associated parameter Figure 1 contains ome sample rules Later rule based systems have attempted to achieve a cleaner

Object rule with a priori certainty factors shown in brack ts

IF 1) th ite f th ltur i the th oat AND
2 the dentity of the o garis t eptcc ccu

THEN th e is ugg sti e ev d nc (0 9) that th ubt pe of
th o nism ct group D

Meta rule for the identity parameter of orga ism states

IF 1) the site of th cultu e i one of the no te le
s tes AND
2) the e are rule which entio in th ir premise a
p evious org ni m whi h ay b the same as the urr rt
organism

THEN it is definit (1 0) that e ch of them i not go ng to be
useful

Figure 1

Example ules from the MYCIN syste

epa atıon b tw en cont ol a d domaın le el knowledg The MYCIN research ıs well known for ıts productıon ule representatıon a d als for ıt ı no atı e model of ınexact reasonıng the calculus of c taı ty fa tors MYCIN became a laboratory for ın stıgatıons ınto knowledg acquısıtıon metalevel reasonıng ıntellıgent computer aıd d nstruct on xplanatıo a d kn wl dg e gıne ıng to l

2 3 2 The MIND System

The MIND ystem [Wılkınson85] ıs a rule ba d exp t system desıgn d for VLSI dıagno ıs It uses shallow knowledg and ıntegrates the prıncıples of hıerarchıcal desıgn and an expert s he rıstıcs to achıeve an effıcıent dıagnostıc procedure The maın elements n the MIND system ınclude th followıng the Check program test system hardware wıth buılt ın self test (BIST) features a test knowledge database a dıagnostıc rule database causal maps an ınference engıne and a user ınterface The Check program ensures that the test system ıs wo kıng at a functıonal level It provıdes stımulus fo the BIST hardwa of the test system and collects test results(symptoms) whıch may ındıcate the mısbehavıour of a certaın functıon wıthout knowıng where fa lt ıs located These symptoms are then stor d ın the test knowledge database for lat r use by a repaır expert ınferenc engıne

A majo feature of this system is its peed in processing rules All rules are converted into integer or a tokenized form and then input to the ference engine This leads to a much faster evaluation of rules

One advantage of this system is that it integrates the expert diagnostic technique with the automatic symptoms detecti n capability Us ng the Ch k p ogram th MIND system c n detect symptoms automatically The proce of a machine int rrogating a us for symptoms wh ch is prone to rors thus ca be avo ded

2 3 3 The GDE System

The General Diagn tic Engine(GDE) [DeKleer87] is a diagnostic system that e ploit deep knowledg But unlike many other systems the space of potential candidates when ncountering the possibility of multiple faults does not grow exponentially with the numb r of faults considered To diagnose multiple faults the features of ATMS (Assumption Based Truth Maint nance System) are used

Measurements are needed to actually d termine if a candidate component is faulty In determ ning the next mea urement whi h leads to th discovery of the faulty omponents us ng minim m number of measureme ts GDE us s an ATMS It incorporates th apriori probabilities of individual component failure such that it can easily compute the onditional probability of a cand date

and th pos ible outcome of m a urements based on a model of the potentially faulty device

This combin tio of probab list c inference and ATMS en bles GDE to apply a mi mum entropy method to dete m ne what measurement to make next The be t m asurement is the one whi h minimizes the expected e tropy of candidat p obabil ties resulting from the measurem nt

2 3 4 CASNET

The CASNET [Weiss78] system is in principle a ge eral tool for building exp t systems for the diagno i and treatment of diseases whos mechanisms are well known It uses deep knowledge Diseas are modelled in terms of Cau al ASsociation l NETworks Such a network is a part ular type of semantic network design d to

descr be dynami processes in terms of (l op free) causal relationships among a s t of internal variables

relat this description to external variables that are considered to be manifestations of the internal processes

descr b various classifications imposed on the dynamic processes

CASNET models can be used to describe pathophysiological processes of disease Knowledge is represe ted by three types of data elements corresponding to the three kinds of description outlined above observat ons of the patient pathophysiolog cal

states and d agnostic prognostic and therapeutic cat go ie Ob ervat ons are the direct dence obtained ab t a patient Path physiolog cal states are interm d ate constru ts that des ibe ternal conditions a um d to take plac in the patient they summarize results from many diff ent observations Cat go es of disease are concept ally at the highest level of ab t a tion summarizing patterns of state and observations

Wh n diagnosis is to be modelled in a domain of knowledge where me hanisms of disease are unde stood the cause and eff ct model can be u d to significantly improv the basis on which decis ons are made How er when less information s available assoc at ons betw n findings must be relied on to a greater extent and th goals of reaching structured and well explained conclusions and recommendations may not be fully satisfied

2 3 5 The Hanna and Gold System

The Hanna and Gold [Hanna88] system is an expert diagnosis system employing both deep and shallow knowledge The system unde diagnosis may be dynamic it s components may have internal states and have varying propagation tim state t ansitions may be asynchronous and feedback loops are allow d at all structural levels

The system consists of two layers a shallow expert(SE) wh ch contains traditional symptom to fault associations along with a

hypothesis t ting mechani m and a deep exp rt (DE) in wh h a hierarchi al model of the diagnosed sy t m represented in multiple l vel of structural and behavi ral abstract on

A multilevel simulator that shifts on demand from coarse q alitative modelling to detailed quantitative modelling assists the diagnosis process in v rification and elimination of hypothesized suspects Knowl dge of pathological behaviour (failur nodes) of lower level components is incorporated i the simulator Learning is exhib ted as deep to shallow expertise transfer as w ll as up the abstraction l vels of the simulator it elf

Integration b tween th DE and SE layers is man fested in two ways (1) The diagnosis process recursi ely navigates through the lev ls of the system s structural hierarchy and at each level switches to deep simulation based e pertise when the current shallow expertise is insufficient for solving the pa ticular level (2) As the deep expertise is being utiliz d n w shallow expert se(i e direct symptom to fault assertion) i automatically constructed augmenting the SE layer for future m r efficient d agnosis The repr sentation language and the inference engines of the two layers are implemented in PROLOG

2 4 Where Present Work Fits In

How r in recent yea research has b en going on diagnostic y tems in which the model incorporates some forms of ncomplet ness Whil in the experient al approach as described above some attempts have been made to deal with ncomplete and imperfect theories [Rajam ney87] the completeness of the model is a common assumption in first p inc ple diagnostic syst ms The assumption holds good in certain problem domains such as electronic troubleshooting and solutions from first principles have been successful Howe r th assumption is inadequate for the application of ontological approach s to complex problems such as medical diagnosis or mechanical trouble shooting Indeed wo king at mult ple levels of abstraction can reduce the computational complexity of the reasoning process But th n one still cannot assume that the lowest lev l of description is complete Abstractions at the lowest level of domain theory imply missing knowledge A further limitation of ontological approaches directly oncerns the definition of diagnosis a a set of faulty component The definition can be on the one hand too restricti e since we may want to distingu h between different faults of th same component on the other hand in many cases the faulty behaviour is not due to a small set of responsible faulty components

The pr s nt wo k a m at pr ıdıng a d agno tıc mecha ısm based n d p au al model of the doma n wh ch sımultaneously ıncorporates some forms of ıncompl ten ss The basıc ıdea ıs ın lınes wıth [C nsol 89] (and also [Console88]) S m ab tra tıo of shallow knowledge from th underlyıng deep model ıs also ınvol ed

The maın goals addressed are

- ıntroducıng a formalısm to represent ıncomplete ca sal knowledge (elaborated ın next chapter)
- gıvıng a log cal foundatıon of causal reasonıng on ıncomplete knowledge
- provıdıng a formal treatment of multıpl fault dıagnos s wıthın ca sal models
- provıdıng crıterıa to select most desırabl solutıon of a problem
- abstractıon of some shallow knowledge after fındıng a sol t on from the deep model

Chapter 3

SYSTEM LEVEL OVERVIEW

In this chapter an overview of the architecture of the diagnostic system d veloped is presented First the theoretical basis is developed Then a system level d scription is provided

Th re seem to be two quite different approache in th theory and design of diagnostic reasoning systems

In the first approach often ref rred to as diagnosis fr m f rst principles one begins with a desc ipt on of some sy tem tog ther with an observation of the system s behaviou If this observation conflicts with the way the ystem is meant to behave one is confronted with a diagnostic problem nam ly to determ ne those system components which when assumed to be f nctioning abnormally will explain the discrepancy between th observed and th correct behaviour For solving this diagnostic problem from first princ ples the only available information is the system description i e its design structure plus the observation(s) of the system behavio In parti ular no heuristic information about system failures is availabl Notable examples of approaches to diagnostic reasoning from first principles are ([Reiter87] [Davis84] [DeKleer85] [Reggia83] etc) We shall call such approaches as ontological ones

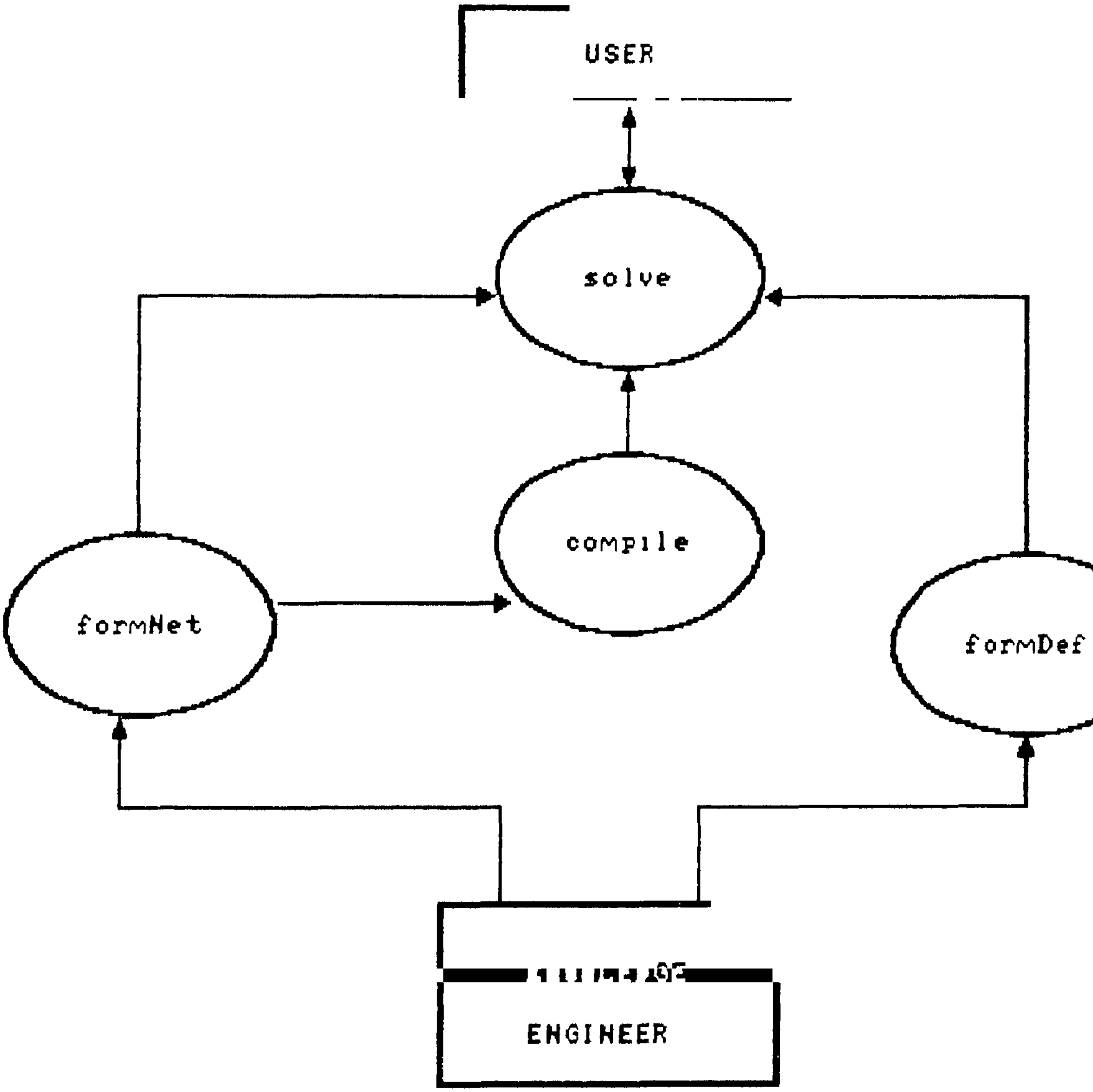

FIGURE 3 A SCHEMATIC DIAGRAM OF THE VARIOUS MODUL

Und r the se ond approach to diagnostic reasoning which might be d cribed as the experiential approach or d agnosis from xperience heuristic information plays a d minant rol Th corresponding diagnostic reasoning systems attempt to codify rules of thumb statistical intuitions and pa t experience

However in re nt years esearch has been going on diagnostic sy tems in which the model incorporate some form of incompleteness This is only natural since many domains are so complex that some form of incompleteness is necessarily engrained in them and any diagnosis based solely on a so called complete model is bound to prov inad quate While in the exp r ential approach some attempts have been made to deal with incompl te and mperfect theories [Rajamoney87] the completeness of the model is a ommon assumption in first principles diagnostic systems The assumption holds good n certain problem domain such as electron c troubl shooting and solutions from first principles have been succ ssful Howe er the assumption is nadequate for the application of ontological approa hes to complex problems such as medical diagnosis or mecha cal trouble shooting Indeed working at multiple levels of abstraction can reduce the computational compl xity of the reasoning process But then on still cannot assume that th lowest level of description is complete Abstractions at the lowest level of domain theory imply mi sing knowledge A further limitation of ontological approaches directly concerns

th defin tion of diagnosis as a s t of faulty components The definition can be o the one hand too r strictiv nce we may want to disti guish between different faults of the same component on the other hand in many ca es the faulty behaviour is not due to a small et of responsible faulty components

Of late so called causal modelling approaches have b en widely adopted in diagnosis especially in m dical domains ([Clancey84] [Fink85]) Such approaches have widely b en applied to many eal world problems but they seem to b less constrained and well defined than ontological ones Some form of incompleteness need to be accommodated in causal models

The present work aims to provide a diagnostic mechanism i a causal modelling formalism with a precise logical formalization but which simultaneously incorporates some forms of incompleteness The basic idea is in lines with [Console89] (and al o [Console88])

3 1 A Formalism to Represent Deep Causal Knowledge

Ca sal network are a general formalism to rep es nt causal knowledge This knowledge may be used to describe the behaviours of a physical or physiological system We discuss how such causal networks can be us d to model the faulty behaviour of a system See the example in Figure 2 There are at least two advantages

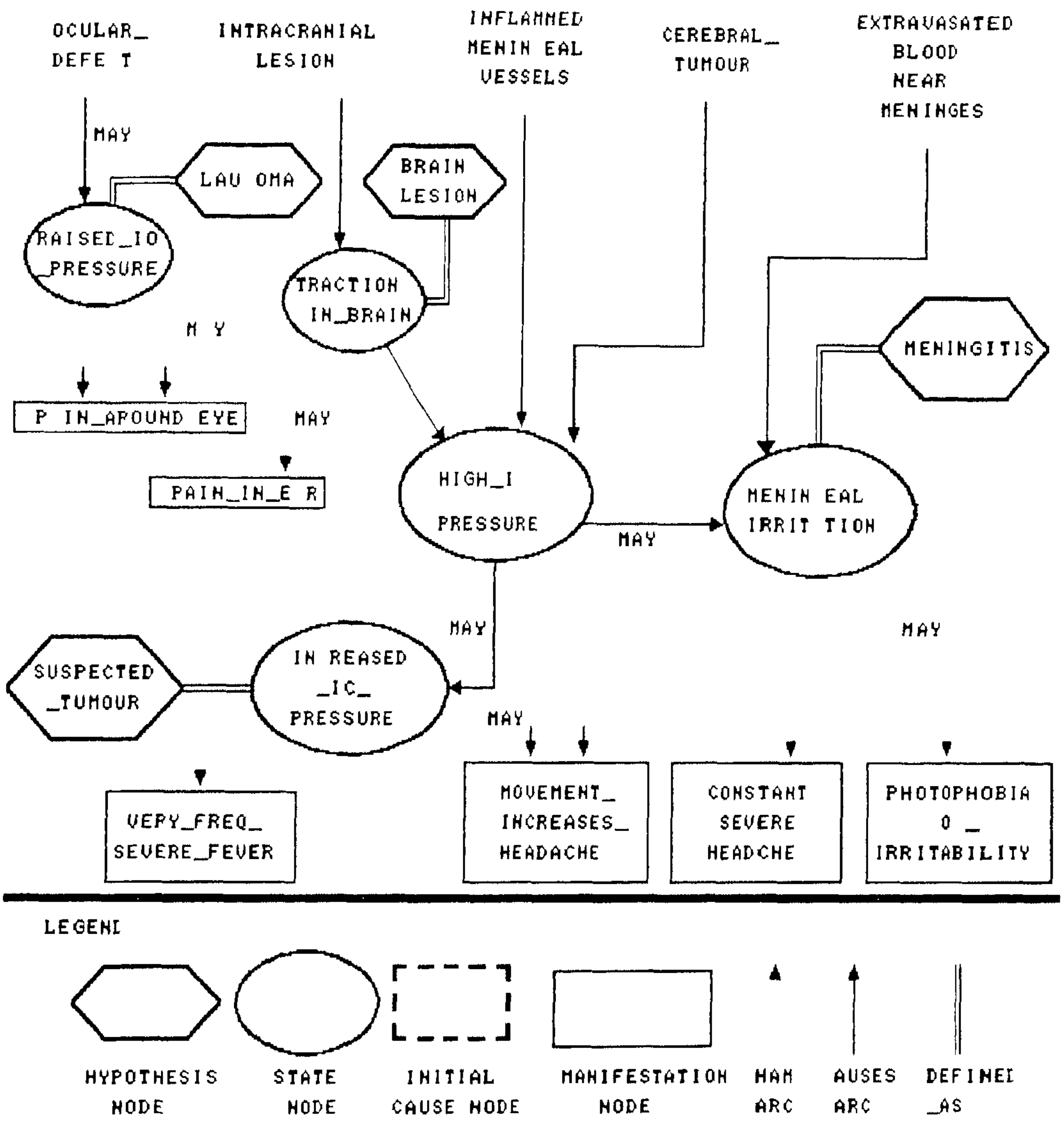

FIGURE 2 AN EXAMPLE CAUSAL NETWORK FROM THE MEDICAL DOMAIN

to this a al net representation h me F rst th system an trace from activated hypotheses backward along cause effe t pathways t identify starting nodes in the network Start ng nodes are hypoth ses for whi h no caus s have be n defined and are thus primary di orders Second if any intermediate node along this path is known to be false this ausal pathway can be ruled out as a candidate explanation for the patient s probl m observations

Four types of nodes are used in this cau al modelling formal sm They are

(i) STATE nodes (elliptic boxes) repres nting partial states of th mod lled yst m (the e states are not observable)

(ii)MANIFESTATION nodes (rectangular boxes) repres nting observable manifestations of internal states

(i i)INITIAL_CAUSE nodes (broken li ed rectangular boxes) representing nitial perturbations the mechanisms starting the p ocesses which might lead the system to a faulty behaviour These are assumed to b non observable introd cing the first form of incompleteness in the mod l Such nodes are abstractions of the actual perturbation processes and th model gives no direct way to establish their presence

(iv) HYPOTHESIS nodes (he agonal boxes) representing diagnostic hypoth ses

The nodes n a netwo k can b conne ted by m an of d ff rent types of ar s (i e r latio h ps) They are

(i) CAUSES arc (continuous arrow) on e ting one or a set (conjunctio) f INITIAL_CAUSE and STATE nodes to a STATE node Th se arcs represent a caus effect r lat onship

(ii)HAM arc (da hed arrow) connecting a STATE node to a MANIFESTATION node These arcs onnect states t their external manifestations HAM stands as an abbreviation of Has As a Manifestation

(iii)DEFINED_AS arcs (double lines) connecting one o a set (conjunction) of STATE nodes to a HYPOTHESIS node These epresent that the hyp thesis is defined a the presence of the states

Hence hypotheses are defined concepts

In case of different arcs entering a node N such arcs are implicitly ORed Besides the incompleteness associated with INITIAL_CAUSE nodes some other form of incomplet ness must b accommodated by causal modelling formalisms Causal model of complex physical or physiological systems may be incomplete at least for the following reasons

Choosing the level of deta l of a m del s domain and task dependent and often subjective Howe er in order to constrain the comple ity of a model some bounds have to be

imp sed to the le l of detail at which knowl dg s represented Hence pro es es and conditions at a lower le el than the chosen one ha to b ab t acted

There exist (especially in phy iol g cal systems) pr ce s and conditions which ar not perfectly known

T deal with such forms of incompleteness th CAUSES and HAM relat ns can be labelled as MAY A MAY label denotes that the model of the relationship is incomplete That is some cond tion o process has been abstracted A relation hip not explicitly lab lled a MAY is assumed to be implicitly labelled MUST i e fully specified

3 2 Diagnostic Problems and their Solutions

Given the r presentation as above a few def nitions are now in place which are to be used later on

Definition [D1]

The set of assumptions is the union of the ets of abstracted conditions and the initial causes

Definition [D2]

Given a diagnostic hypothesis H the definition of H denoted by def(H) is the set {S1 Sk} of STATE node S1 Sk which are connected to H by DEFINED_AS arcs

Definit o [D3]

A diagno tic problem (d p) P s a triple <NET HYP OBS> where

NET set of nod s and arcs modelling the cau l n twork NETWORK

HYP { <H def(H)> | H is a HYPOTHESIS node in the causal network NETWORK }

OBS a nonempty set of ground manifestations i e observations Thus OBS is always a subset of MANIFSET the set of all MANIFESTATION nodes

Since man festations repres nt obse vable conditions we assume that manifestations not declared as observed are ab ent The set of manifestations not obser ed is thus given by

ABSENT MANIFSET OBS

This assumption introduces non monotonicity in the diagno tic process in order to draw conclusions from incomplete knowledge That is we only have a partial description of the case under examination

A hypothetical world may be regarded as a tentative econ tructi n of the causal evolut on that has led to the obs rved situation The notion of hypothetical w rld s def ned recursively The basis is the case of a world containing initial causes the recursive case involves abstracted cond tions on causal relationships

Definition [D4]

Gi en a d p P < NET HYP OBS > and g ven a world W W a world for P ff

W NET U {c1 c2 ck} where ci for i 1 k s a gro nd initial ca se (in this case we say that W is an initial world for P) or

W W1 U {A} where

W1 is a world for P

X & A > Y is an instance of a formula in NET where A s an abstracted onditi n ymb l W1 I X

In the latter case of the definition the world W1 U {A} has to be considered in order to examine the consequences of assuming that the condition A is actually true in the case under examination that is assuming that the corresponding MAY condition in the CAUSES or HAM relationship holds in th case under observation

Definition [D5]

Given a diagnostic problem P < NET HYP OBS > a world W for P is inconsistent iff W I - m for some ground manif station m such that m s not an element of OBS

That is W is inconsistent for P iff W does not deri e any manifestation which has not been observed and henc logically inconsistent

Def nition [D6]

Gi en a world W and a set OBS of observations W covers OBS iff for all element m in OBS W | m

Definition [D7]

Given a diagnostic problem P < NET HYP OBS > a world W for P is a final wo ld iff W covers OBS and is not inconsistent that is

OBS { m / m is an observation W | m }

Thus a final world W for P has to explain all the observed findings and must not predict the presence of manifestations that have not been found

Defin tion [D8]

Given a diagnostic problem P < NET HYP OBS > and a final world W for P a solution to P is given by the set

diagnosis(W) { H / <H def(H)> is an element of HYP
W | def(H) }

Then W is said to be a causal explanation of the solut on

3 3 Parsimonious Solution

There may be mor than one final world and then more than one solution to a diagnostic problem according to the definitions given above A solution is one of the possible explanation of the given data Thus we need to have some criterion with which we can say that one solution is better or more acceptable than

a oth r Th n we an have a diagnostic algor thm which would allow us to have a solution which is bett r th n all other solut ons in the yardstick of the criterion

The criter on chosen is that of parsimony W would like to choose that soluti n whi h would involve the least number of assumptions over the conditions The problem is that we have no direct way to establish the truth of the onditions that have been assumed in order to explain the observed find ngs The a sumptions made a e on INITIAL_CAUSE nodes or on MAY arcs Let us r call what the INITIAL_CAUSE nodes s gnify They are abstractions of actual perturbation pro esses and the model g ves no direct way to establish their presence Now in many cases it i quite reasonable to assume that th se perturbat ons are ndependent of each oth r We too would derive sol tions based on this assumption

Each of these INITIAL_CAUSE nodes potentially giv s rise to several MAY arcs which in turn form links n the paths to manifestations that have b en observed It is then more desirable that we select those INITIAL_CAUSE node earlier which potentially explain more of the observations Th s is b cause of the assumption of independen e we made above The s lution arrived at in this manner would then be parsimonious over INITIAL_CAUSE assumptions We call such a solution an IC Parsimonious solution

3 4 Problem Formulation & Generation of IC Parsimonious Solution

The system can be used to formulate a diagnostic problem and generate an IC Parsimonious solution The following modul s show how this is done A schematic diagram is provided in Figure 3

Module 1 Formation of the network

This module interactively lets the user form the network of the diagnostic problem domain The network is grad ally fo med by asking the user to create a node and a king if further nodes are to be input

Module 2 Defining the hypotheses

The definition of th hypotheses in terms of the various STATE nodes can be specified in this module These model the DEFINED_AS arcs of the network These relationships are at a different knowledge level than the other ones in the network and so are represented in a different manner

Module 3 Compiling the network

This module compiles the network to form various l sts Th knowledge acqu red so far in the two previous mod ls is of a static nature in the sense that unless the underlying structur of the network changes the acquired knowledge does not change So it is advantageous to have compact chunks of knowledge that are derivable from the existing knowledge This eliminates the need to unnecessarily repeat this process each t me observations are acquired

Module 4 Entering the observations

The manifestations wh ch have been ob erv d are input thi module This along with the first two modul s complete the formulation of th diagnostic problem

Module 5 Generating the IC Parsimonious solution

This module uses the knowledge compiled in Module 3 and generates the IC Parsimonious solution The solut on is ach eved in iteratio s of set covers over the set of all ob ervations The solution obtained is added as a shallow rule to the knowledge base so that when a solution is asked for the same et of observations the system consults the shallow knowledge to provide the solution

N te that as the set of observations change the IC Parsimonious solution als changes In particular when more observations ente the set OBSV some of the hypotheses confirmed arli may no longer by predicted This is consistent with the monotoni ity that was introduced with the assumption that manif stations which are not declar d as observed are absent

3 5 An Example

Consider the following example from the medical domain The causal model tries to capture some of the knowledge req ired to

dıagnose a lments who e symptom ccur as varıous f rm of h adach s Please refer t Fıg e 2

The ınıtıal_caus s are ocular_defect ntracranıal_lesı n ınflammed_menıngeal_ve sels cerebral_tumour and extravasat d_blood_near_menınges These are ınıtıal perturbatıons to the ystem and accordıng to our assumptıon not verıf able The observable manıfestatıons are paın_ar und_ey paın_ın_ear very_f equent_and_s v re_headache movement_ıncreases_h adache constant_severe_headache and photophobıa_or_ırrıtabılıty The hypotheses are glaucoma (defın d by the state raısed_ıntraocular_pressure) suspected_tumour (defıned by th state ıncr ased_ıntracranıal_pressure) braın_l sıon (d fın d by the state tractıon_ın_braın) and menıngıt s (defıned by the st t menıngeal ırrıtatıon) The dıfferent causal arcs whıch are labelled may are the may arcs Those not labelled are the must arcs

Chapter 4

Implementation Details

In this chapter the implementation details of the various system modules of th diag ost system are presented The system is dev loped on HP 9000 erie in IF/Prolog ([Clocksin84]) Sample sessions are provided in the appendices Befor we come t a module wise des ption of the system let us briefly t uch upon the data structures us d

4 1 Data Structures

The two main data structures us d are f ames and li ts The network has been implemented in terms of fram s Each frame has the following optional slots

isa	to describe the type of node
causes	to repr sent the CAUSES ar
ham	to represent the HAM a c

Each slot has an attribute and a alue The attribute in case of a isa slot is optional and in cas of causes and ham slots can be must or may Th value in case of isa slot is the type of the node in ca e of causes slot it is a STATE node while i case of a ham slot it is a MANIFESTATION node

Lists have been used xtens vely to hold both local and global data structures Prolog cla ses have been used to create data bases of facts

4 2 Implementation of the Various Modules

Th implementation details of the various modules follow

4 2 1 Module formNet

This is the module which interactively lets the user form the network of the diagnostic problem domain The network is gradually formed by asking the user to create a node and asking if further nodes are t be input While creating a node the user s successively asked to input the slots Proper validation is done while accepting the user input for the slot attribute and value However it s the onus of the knowledge engineer to create proper links between the network nodes and assign proper types for the nodes This is because it is not possible to k ow beforehand the characteristics of the network n an arbit ary problem domain

The following are the main routines used in this module

1 form_network

Form the network interactively

2 enquire_more_nodes(Ans)

Ask user if network formation is over and act depending on answe Ans

3 form_a_node

Form one node of the network

4 enter_slots(Node)

Enter the slots for this node Node

5 nter_a_slot(Node)

Enter one slot of the node Node

6 enquire_more_slots Node Ans)

Ask user if all slots for the node Node has been entered and act depending on answer Ans

7 check_slot(Slot)

Validate the slot Slot

8 ch ck_attrib(Slot Attrib)

Validate the attribute Attribute for slot Slot

9 check_value(Slot Value)

Validate the value Value for slot Slot

4 2 2 Module formDef

This module lets the knowledge engineer form th definitions of the hypothesis Each hypothesis is defined as a conjunction of several STATE nodes The final aim of the diagnosis is to generate a set of hypotheses as solution While asking for definitions of the various hypotheses the system validates input in the context of the network already formed

The following are the main routines used in this module

1 form_all_definitions

Ask user to input the hypotheses and form their definitions

2 form_a_definition(H StateSet)

Form the definition for hypothesis H and validating against StateSet

3 get_definition_states(H Stateset)

Get the states the define the hypothesis H alidating against StateSet

4 enqu re_mor _states(H Stateset)

Enquire if more states are needed to define the hypothesis H

5 check_state(S StateSet)

Validate state S against StateSet

4 2 3 Module compile

This module compiles the knowledge entered so far in the modules formNet and formDef into chunks of knowledge to be later used in the diagnostic process This part of the work is common across all diagnostic probl ms in where the causal netw rk of the pr blem remains unchanged For all such cases compiling the network is n one time effort The actual diagnostic process can use the knowledge compiled to save a lot of repetitive work In part cular this module fo ms two li ts corresponding to each INITIAL_CAUSE node

MustL st   this list contains a list of paths from the INITIAL_CAUSE node to the reachable MANIFESTATION nodes that contain no MAY arcs

MayList   this list contains a list of paths from the INITIAL_CAUSE node to the reachable MANIFESTATION nodes each of which contains at least o e MAY arc

The following is the main routine used in this module

1 formMMl st(InitCause Manif MustList MayList)

Form the Must May lists g ven an initial cause InitCause and manifestation Manif

4 2 4 Module getObs

This modul allows the user to get the set of manifestations that ha e been observed The manifestations not observed are assumed to be absent This completes the specification of the diagnostic problem This the part of the diagnostic problem liable to change more frequently than other parts

Th following are the main routines used in this module

1 get_ob ervations

   Get the observations

2 enquire_manifestations(L)

   Enquire if th manifestations in the list L have been observed

3 enquire_a_manif(M)

   Enquire if the manifestation M has been observed

4 2 5 Module solve

This is the main module which actually gets the solution Note that the solution cons sts of a set of hypothesis confirmed and hence involves multiple fault diag osis Moreover the diagnosis is non monotonic It makes use of the knowledge compiled in the module compile

Th module uses the following algorithm

1 Partition the set of all INITIAL_CAUSEs into two sets VALID and INVALID wh re

VALID {IC | IC is an INITIAL_CAUSE node

MustLeaves(IC) is a subset of OBSV }

INVALID OBSV VALID

OBSV set of all MANIFESTATIONs observed

MustLeaves(IC) set of the last nodes in the elements of MustList(IC)

MustList(IC) paths from the INITIAL_CAUSE node to the reachable MANIFESTATION nodes that contain no MAY arcs

2 Form the set VM where

VM union of MustLeav s(IC) over all IC where IC is an element of VALID

3 Form the set DIFF OBSV VM

/* If DIFF is a null set then solution is unique else there can be several ways to cover DIFF by forming unions over MANIFESTATION nodes that may be eached from the INITIAL_CONDITION nodes We look for the cover which is most parsimonious in the INITIAL_CONDITION nodes */

4 Let

INIT < VALID

ADDITIONAL < NULL

5 Let

MayLeaves(IC) set of the last nodes in the elements of MayList(IC)

where

MayList(IC) paths from the INITIAL_CAUSE node to the reachable MANIFESTATION nodes that contain at least one MAY arc

6

/* find the set ADDITIONAL whi h wo ld be containing INITIAL_CAUSE nodes required in addition to those in VALID t get a solution

Those INITIAL_CAUSE nodes are chosen earlier which may l ad to larger sets of MANIFESTATION node that ha b en ob erved */

R p at until DIFF NULL

begin

for all IC in INIT do

form the s t MayDiff(IC)

where

MayDiff(IC) intersection of the sets MayLeaves(IC) and DIFF

Find ICk belonging to INIT such that

MayDiff(ICk) has the max mum cardinality among all MayDiff(IC)s for ICs in INIT

ADDITIONAL < nion of ADDITIONAL and { ICk }

INIT < delete ICk from INIT

DIFF < DIFF MayDiff(ICk)

if INIT is null and DIFF is not null then

INIT <   INVALID

end

7 Find the set Impo Nodes where

ImposNodes set of all nodes that an never be included in any possible cover

/* These are the nodes that must lead to observations that have not been observed and hence according to our assumption absent */

8 ValAd < union of VALID and ADDITIONAL

Cover d < null

9 For all IC in ValAd do

begin

put all nodes in all paths from IC to MustLeaves(IC) which are not already in Co ered in the set Covered

let MayObs(IC) intersection of the sets OBS a d MayLeaves(IC)

put all nodes in all paths from IC to MayObs(IC) whi h are not already in Covered in the set Covered

end

/* the set Covered now contains all nodes in the network which has been covered in forming th solution and form a final world for the diagnost c problem (Definition 07)*/

10 Let HypoSet   et of all HYPOTHESIS node

Def(H)   set of all STATE nodes that define the HYPOTHESIS node H

Solution <   null

11 For each eleme t H in HypoSet do

f D f(H) is a subset of Covered then put H in Solution

1 Output the s t Solution which c ntains the IC Parsimonious solution

13 Add a shallow rule to the knowledge base abstracting the connection between the observations and the solution

While the solution is being formed a trail of th hypotheses entering the set Solution is displayed

The following are the main routines used in this module

1 get_path(Start Dest Route)

Get the path from Start to Dest in Route

2 check_hypotheses(S)

Form the IC Parsimonious hypothesis set S

3 cover_all_paths(L)

Cover all paths starting from elements of the list L

4 assert_all(IC L)

Assert all paths starting from IC to elements of the list passed as the second parameter

5 formHypoSet(HypoSet)

Form the set of all hypothesis

6 cover_a_path(IC Obsv)

Cover a path from IC to Obsv

7 m x_cardinality(IL Diff ICmax MDmax Cmax)

Find the initial condition ICmax having max cardinality of set MD among all ICs in IL the MD set corresponding to ICmax is returned in MDmax and the cardinality of the set MDmax is returned in Cmax

8 formAdditional(ValidSet VMust Init Addl)

The set Addl will contain the additional ICs required to cover all the observations

9 formMD(IC MD Diff)

Form the set MD

10 formDiff(VMust Diff)

Form the set Diff

11 assertValidInvalid(ValidSet InvalidSet VMust)

Form the sets Valid Invalid and VMust

12 formICmustSet(IC ICmustSet)

13 formICmaySet(IC ICmaySet)

Form the Must May lists for a given initial cause IC and a set of manifestations the lists contain the whole paths from the IC to manifestations

14 formICmustLeaves(IC ICmustLeaves)

ICmustLeaves contains only the manifestations that must b reachable from an initial condition IC

15 formICmayLeaves(IC ICmayLeaves)

ICmayLeaves contains only the manifestations that must b reachable from an initial condition IC

16 form_one_ic_list(IC [] MustLists MayLists)

Form the MustList and MayList for one initial_cause

17 formObsvSet(ObsvSet)

Form the set of all observations

18 formManifSet(ManifSet)

Form the set of all manifestations

19 formImposLeaves(ImpL)

Form the set of all impossible leaves the manifestations that have not been observed

0 formImposNodes(ImpN)

1 assertImposNodes(ImpN)

Form and assert the set of all impossible non_leaf nodes these nodes must lead to manifestations that have not been observed

Chapter 5

CONCLUSIONS

5 1 Conclusions

The present work aims at providing a diagnostic mechanism based on a deep causal model which simultaneously incorporates some forms of incompleteness

The main goals addressed are

introducing a formalism to represent incomplete causal knowledge

giving a logical foundation of causal reasoning on incomplete knowledge

providing a formal treatment of multiple fault diagnosis within causal models

providing criteria to select most desirable solution of a problem

abstraction of some shallow knowledge afte finding a solution from the deep model

Traditional diagnostic systems have followed either the approach of reasoning from first principles with hardly any ncompleteness in the model or the approach of reasoning guided by heuristics which lack in formulation of a deep model of the system under diagnosis This work tries to explore diagnostic reasoning from

Chapter 5

CONCLUSIONS

5.1 Conclusions

The present work, aims at providing a diagnostic mechanism based on a deep causal model , which simultaneously incorporates some forms of incompleteness.

The main goals addressed are :

- introducing a formalism to represent incomplete causal knowledge ;
- giving a logical foundation of causal reasoning on incomplete knowledge ;
- providing a formal treatment of multiple-fault diagnosis within causal models;
- providing criteria to select most 'desirable' solution of a problem;
- abstraction of some shallow knowledge after finding a solution from the deep model;

Traditional diagnostic systems have followed either the approach of reasoning from first principles with hardly any incompleteness in the model or the approach of reasoning guided by heuristics which lack in formulation of a deep model of the system under diagnosis. This work tries to explore diagnostic reasoning from

first principles in a deep causal model of th system th incorporates two forms of incompleteness in the model The fir form of incompleteness is the assumption that initi perturbations that result in malfunctioning of the system are observable The other incompleteness is the ass mption th certa n causalities a e not precisely known That s gi en t states for the syst m one may give rise to th other but ne not nec ssarily do so This only implies that certain conditio are being abstracted Such abstraction is sometimes done in orc to constrain the complexity of th model On other o a i where the processes and conditions are not perfectly known (f example in physiological systems) such abstraction cannot avoid d

The diagnostic process as described n the pre ent work s nc monotonic in the sense that a solution for a pr blem need not subset of a solution of a problem whose set of observat ons is superset of the observations of the former Also si ce the moc inco porates incomplete knowledge there may be multip solutions to the same problem (Howev r each solution mi consist of multiple faults) Now mong all such solutions w ne to find out the one which is best in some s nse The criteri of parsimony is often used to rank solutions In this case have chosen parsimony based on nitial causes and the solut obtained is termed IC Parsimonious solut on The reason why tl

criterion is chosen, is that the initial causes are not observable according to our assumption. Each such initial cause potentially gives rise to manifestations which must be observed or which may be observed. The parsimony is enforced by first including the initial causes whose "must" manifestations (that is those manifestations which must be observed if that initial cause is actually present) have been observed, followed by including the initial causes with observed "may" manifestations (i.e.,those manifestations which may be observed if that initial cause is actually present) in the set of nodes covered.

The other aspect is the realisation that it is not always that a diagnosis is based on a deep model of the system. One tries to reason on a shallow model as long as one can afford, and fall back on the deep model when the shallow knowledge does not suffice. This means that for a problem not known before the diagnosis necessarily goes on a deep model. But next time when the problem is encountered, the reasoning goes on a shallow model. So when a new problem is faced , apart from diagnosing on a deep model, some knowledge is abstracted and put in the shallow model of the system. The present work aims at doing this by abstracting shallow knowledge (rules) from a diagnosis based on deep, incomplete causal model of the system. Note, that the solution is the same for a given problem, whether deep or shallow reasoning is involved. In case shallow reasoning can provide a solution, it is as good or as bad as that of the deep model.

However reasoning based on a deep model can potentially provide d eper explanations than reasoning based on a shallow model

5 2 Improvements and Scope for Future Work

The diagnostic system de eloped can be improved in several ways First and foremost good explanation facility can be provided as reasoning goes on One can also explore multi paradigm representations of both deep and shallow knowledge and also reasoning in which both deep and shallow knowledge cooperate The other aspect is trying to quantify the incompletenes in the model in some way and generate some confidence measures associated with solutions One can explore assigning confidenc measures associated with the must and may arcs and combining these measures in some way as the reasoning goes on In that case a parsimony criterion may be based on minimality of th combination of such measures However assigning the measures and combining them suitably do remain open to subjective judgements

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APPENDIX A

Sample Network Formation

```
/*
*************************************************************

   Here is part of a sample session for forming a network

*************************************************************
*/

? formnet

Enter the node name


Node        ocular_defect


Enter the slots for this node

Slot Name     isa

Attribute

Value         initial

Permitted values are   [ initial_cause state manifestation ]
Please enter again

Value         initial_cause

More slots to enter ? [y/n]
y
Node   ocular_defect


Slot Name     causes

Attribute     may

Value         raised_io_pressure

More slots to enter ? [y/n]
n
Mo e nodes to enter ? [y/ ]
y
Enter the node name


Node       raised_io_press re
```

```
Enter th  slots for this node

Slot Name     isa

Attribute

Value          stat

More slots to enter ? [y/n]
y
Node    raised_io_pre sure


Slot Name     causes


Attribute     must

Value         pain_around_eye

More slots to enter ? [y/n]
n
More nodes to enter ? [y/n]
y
Enter the node name


Node        pain_around_ ye


Enter the slots for this node


Slot Name     isa

Attribute

Value          manifestation

More slots to enter ? [y/n]
n
More nodes to enter ? [y/n]
n
?
```

APPENDIX B

Sample Diagnostic Session

```
/*
***************************************************************

Here is a session of diagnosis for the network shown
in figure 2

***************************************************************
*/

/* load all relevant files */

? demoha
consult  file nsha loaded in 1 sec
consult  file formdef loaded in 0 sec
consult  file getobs loaded in 0 sec
consult  file hanet loaded in 1 sec
IF/Prolog Version 3 4 2 HP 9000/800 created 1/9/88
Copyright (C) 1984 88 InterFace Computer GmbH


/*   form the definitions   */

? fd


Enter the hypotheses

Hypothesis   glaucoma

Any more hypothesis ? (y/n) y

Hypothesis   brain_lesion

Any more hypothesis ? (y/n) y

Hypothesis   suspected_tumour

Any more hypothesis ? (y/n) y

Hypothesis   meningitis

Any more hypothesis ? (y/n) n

The list of hypotheses is

[glaucoma brain_le ion suspected_tumour meningitis]

Press <Return> to continue
```

Definition for the hypothesis glaucoma

Enter th states that def ne this hyp thesis glaucoma

Enter State   raised_io_pressure

More states for this d finition of glaucoma ? n

Definition for the hypothesis brain_lesion

Enter the states that define this hypoth s s brain_lesion

Enter State   traction_in_brain

Defin tion for the hypothesis glaucoma

Enter the states that define this hypothe is glaucoma

Enter State   raised_io_pressure

More tates for this definition of glaucoma ? n

Definition for the hypothesis brain_l sion

Enter the states that define this hypoth sis brain_lesion

Enter State   traction_in_brain

More states for thi definit on of brain_lesion ? n

Definition for th hypothes s su pected_tumour

E ter the stat s that define this hypothe s suspected_t mour

Ent r State   inc eas d_ic_pressure

More states for this definition of suspected_tumour ? n

```
Definition for the hypothesis meningitis
------------------------------

Enter the states that define this hypothesis meningitis

Enter State : meningeal_irritation

More states for this definition of meningitis ? n


No more hypotheses !!

yes

/* compile the network to form different lists */

?- compile.
The lists for the initial condition : ocular_defect
=====================================================

 MustLists :
 -----------

[]

Press <Return> to continue ...

 MayLists :
 -----------

[[ocular_defect,raised_io_pressure,pain_around_eye]]

Press <Return> to continue ...
The lists for the initial condition : intracranial_lesion
=====================================================

 MustLists :
 -----------

[]

Press <Return> to continue ...

 MayLists :
 -----------

[[intracranial_lesion,traction_in_brain,high_ic_pressure,
  meningeal_irritation,photophobia_or_irritability],
 [intracranial_lesion,traction_in_brain,high_ic_pressure,
  meningeal_irritation,constant_severe_headache],
 [intracranial_lesion,traction_in_brain,high_ic_pressure,
  meningeal_irritation,movement_increases_headache],
 [intracranial_lesion,traction_in_brain,high_ic_pressure,
  increased_ic_pressure,very_frequent_severe_headache],
 [intracranial_lesion,traction_in_brain,pain_in_ear],
 [intracranial_lesion,traction_in_brain,pain_around_eye]]
```

```
Press <Return> to continue
The lists for the initial condition   inflammed_m ningeal_vessels


 MustLists


[]

Press <Return> to continue

 MayLists


[[inflammed_meningeal_vess ls high_ c_pressu e
  meningeal_irritation  photophobia_or_i rritability]
 [inflammed_meningeal_vessels high_ic_pressure
  meningeal_irritation constant_severe_headache]
 [inflammed_meningeal_vessels high_ic_pressure
  meningeal_irritation movement_increases_headach ]
 [inflammed_meningeal_vessels high_ic_pressure
  increased_ic_pressure very_f equent_severe_headache]]

Press <Return> to continue
The lists for the initial cond tion   cerebral_tumour


 MustLists


[]

Press <Return> to continue

 MayLists


[[cerebral_tumour high_ic_pressure men ngeal_i rritation
  photophob a_or_irritability]
 [cerebral_tumour high_ic_pressure meningeal_ir itation
  constant_severe_headache]
 [c rebral_tumour high_ic_pressure meningeal_irritat o
  movement_increases_headach ]
 [cerebral_tumour high_ic_pressure increased_ic_pre sur
  very_frequent_severe_h ada he]]
```

```
Press <Return> to continue ...
The lists for the initial condition : extravasated_blood_near_meninges
=====================================================

 MustLists :
 -----------

[[extravasated_blood_near_meninges,meningeal_irritation,
  constant_severe_headache],
 [extravasated_blood_near_meninges,meningeal_irritation,
  movement_increases_headache]]

Press <Return> to continue ...

 MayLists :
 -----------

[[extravasated_blood_near_meninges,meningeal_irritation,
  photophobia_or_irritability]]

Press <Return> to continue ...

yes

/* get the observations  */

?- getobs.

The list of manifestations is :
-----------------------------

[pain_around_eye,pain_in_ear,very_frequent_severe_headache,
 movement_increases_headache,constant_severe_headache,
 photophobia_or_irritability]

Which of these manifestations have been observed ?

Observed pain_around_eye ? [y/n] n

Observed pain_in_ear ? [y/n] n

Observed very_frequent_severe_headache ? [y/n] n

Observed movement_increases_headache ? [y/n] y

Observed constant_severe_headache ? [y/n] y

Observed photophobia_or_irritability ? [y/n] y

No more manifestations !!
```

```
yes

/* now solve the problem */

?  solv
ValidSet         [extravasated_blo d_near_meninges]
InvalidS t       [ocular_defect  ntracranial_lesi n
                  inflammed_meningeal_ve sels cer bral_tumour]
VMust            [constant_severe_headache movement_increases_headache]

Imp  sible non_leaf nodes   [inc eased_ic_pressure rai ed_ o_pressu e]

Cove ed List    [photophobia_or_irr tability  movement_increases_he dache
                 constant_sev r _h adache meningeal_irritation
                 e travasat d_blo d_n a _meni ges dummy]
Pres  <Ret  n> to continue

 The Trail of confirm d hypoth se  so far   [meningitis]

Press <R turn> to continue

 The IC Pars mon o s hypothesis set   [meningitis]
ye

/*  ext time if tre same problem i  solved  shallow
   knowledge is consulted to pro  de the solution
*/
?   olv
 The confirmed hypothesis set   [meningitis]
yes

/* end session */
?  by
```

Date Slip

This b ok is to be returned n the d te last tamped